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Mobile Augment Reality Sign Recognition System

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Abstract: This project highlights the problems that are encountered in a typical Traffic Sign Recognition System like incorrect interpretation of a particular traffic sign which is observed by a driver while driving a vehicle causing misunderstanding thereby resulting in road accidents. The visibility is affected by many environmental factors such as smoke, rain, fog, humid weather, dust etc. and it is very difficult to understand the traffic signs in this situations, causing misinterpretations of the particular traffic sign and resulting in road accidents. In order to avoid this condition, a novel method of recognizing traffic signs is developed which take into consideration the color and shape of the traffic sign. Hough algorithm is used for classification of different groups of traffic signs which are predefined by a particular set of features after the process of Image Segmentation. Finally, the simulations of traffic sign images are prepared by using the software tool called as MATLAB.

Key world: Mat lab tool, traffic sign

I. INTRODUTION

Autonomous driving researches are focused either on off-road driving [1] or driving in urban traffic [2]. Thanks to the DARPA Grand Challenge and the DARPA Urban Challenge [3], significant progress have been made in both domains. Autonomous vehicles equipped with several cameras, sensors, and processors prove to move successfully from a starting point to a predefined destination.

There is a remarkable amount of work regarding autonomous driving and its sub-tasks. Most of these studies target the task of moving the vehicle from one point to other, just by avoiding collisions and following the most efficient path. This requires optimal path planning and obstacle avoidance algorithms, but not necessarily the recognition of traffic signs or pedestrians. DARPA Urban Challenge has mandated some specific rules, most importantly "lane following", but has not covered the traffic rules as a whole. Recognition of traffic lights and signs, and recognition of pedestrians are officially left out of scope.

Following the progress in this field, car manufacturers have recently started deploying more intelligence in their latest models. Parking assistance, adaptive cruise control, emergency brake assist, lane departure warning and speed limit monitoring are among the new features appearing in the car market [4, 5]. All of these systems are at the very early stages of their evolution. Much more progress is on the horizon. For example, in the near future, lane, speed limit and traffic light violations are going to be immediately detected by cars and reported to a central traffic regulation system with wireless media.

With these expectations in mind, Automatic Driver Evaluation System (ADES) aims to take a key role in this hot topic of the intelligent car technology. The final product of the ADES Project will be a framework for evaluating the drivers against the traffic rules as they drive. It can be used for;

- Assisting drivers to drive more safely,
- Informing traffic central about the violations (lane, speed, light, other rules),
- Automation of driver license examinations,
- Highway maintenance: to check the presence and condition of the signs,
- Supervising the development of autonomous urban driving.

This study is a part of the ADES Project and is focused on the road lane and traffic sign detection and tracking systems. Two different concepts of autonomous driving challenge are studied and have yielded promising results.

II. METHODOLOGY

Hough Transform Overview

Hough Transform (HT) [7] is a technique to detect arbitrary shapes in images, given a parametrized description of the shape in question. Hough transform can detect imperfect instances of the searched shapes. Besides, HT is tolerant of gaps, and image noise has minor effect on the output.

The simplest form of the HT is the line transform, where lines are the target elements sought by the transform. Representing a line in polar form (Equation 3.1) specifies its normal passing through (x, y) drawn from the origin to (r, θ) in polar space. These are represented by the dashed lines in Figure 3.1.

$$x\cos\theta + y\sin\theta = r \quad (3.1)$$

For each point in the (X, Y) plane and on the line, the values of r and θ are constant. Therefore, for a given point in the (X, Y) plane we can calculate the lines passing through the point in terms of r and θ. Passing a range of lines at varying angles [0, 2π] and varying θ accordingly it is then possible to calculate the value for r. By taking a set of lines through a point and calculating the r and θ values for the lines at that point a Hough space can be created (Figure 3.1). Distributing the results of these calculations to "bins" and incrementing their value or "vote" for every result that is placed in them, an accumulation array can be built. The greater the vote value of the bin, the higher the probability that it is a point on the line.

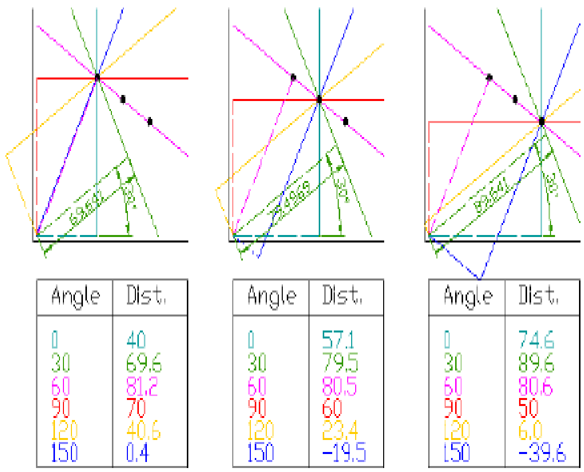

Figure 3.1. Liner Hough transform.

Detection: Multiresolution Hough Transform (MHT)

The classical HT approach processes the entire vision data in order to detect the lines. This scenario has two main drawbacks. First, the occluded lines (i.e. another car passing through the line) become noisy since the transformed relative intensity of the line decreases. Second, the relative intensity of the lines also decreases at the curves in the road.

The proposed solution divides the road image into partitions, where the sizes of the partitions are inversely proportional to the distance of the partition to the vehicle. After the image is partitioned, several preprocessing steps are required before applying the Hough transform. These preprocessing steps should be fast because the Hough transform is already computationally expensive for real time applications. Since edge detection techniques are also usually computationally expensive for real time applications [51, 52], each partition is converted to binary images via applying a threshold filter after a color remapping process.

After the image is partitioned, a separate Hough transform is applied to each single partition. The most intense line in each partition, which is the candidate line segment, is taken into consideration in order to find the global lanes in the image. Since the Hough lines are represented in polar coordinates (r, θ) instead of rectangular coordinates (x, y), the candidate lines are grouped according to their slopes and distances to the center of the image as well as their intensities. The center of the frame is chosen as the reference point.

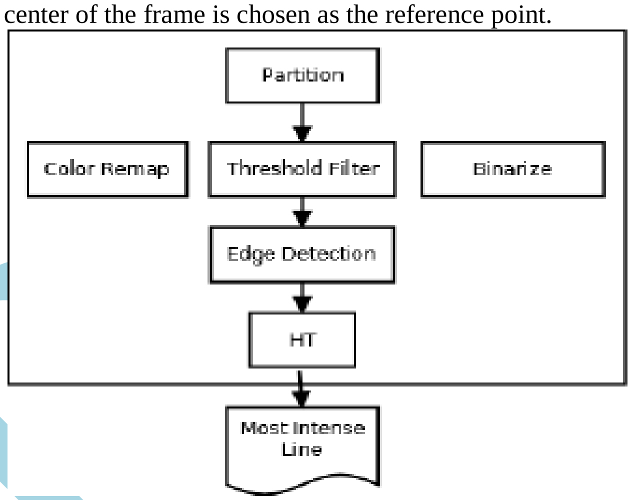

Figure 3.2. Block Diagram for Multiresolution HT.

The transformation of the lines basically changes the center point of the polar coordinates for each transformed line which is achieved by the following translation

$$r' = r + (x - x')\cos(\theta) + (y - y')\sin(\theta) \quad \theta' = \theta \quad (3.2)$$

where (r', θ') are the global polar coordinates (with respect to the reference point) of the Hough line (r, θ). Note that the translation of the center of the Hough transform is from (x, y) to (x', y').

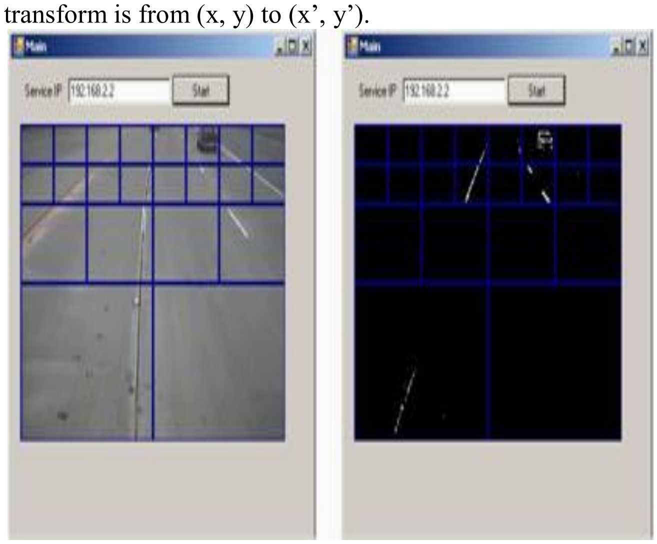

Figure 3.3. (a) Partitioned image, (b) Binary image.

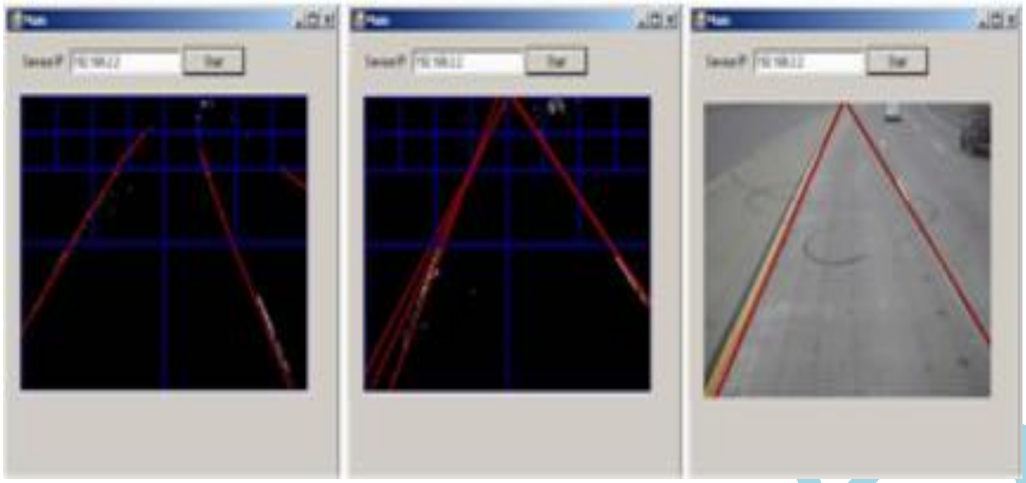

Figure 3.4. (a) Candidate lines, (b) Transformed line, (c) Detected lines.

After the lines are grouped, the most intense three clusters are assigned as the lanes. However, there may be less than three lanes if the sum of the intensities of the candidate lines is less than a threshold value.

Tracking: HMM

HMM [53] is an alternative to Kalman filter and particle filtering. It is a statistical model in which the system being modeled is assumed to be a Markov process with unobserved states. As shown in Figure 3.5, the system consists of predefined sets of states and observations. A state transition probability matrix defines the probabilities of transition between states. An emission probability matrix defines the probability of encountering each observation for each state. System also defines the start probabilities of each state. The ultimate aim of an HMM is to estimate the next observation relying on the current observation, without access to the state information.

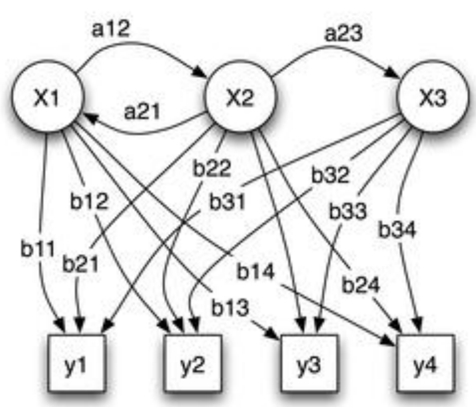

Figure 3.5. Hidden Markov Model. (x: states, y: possible observations, a: state transition probabilities, b: emission probabilities)

For lane tracking, HMM is used to represent the relation between the current frame and its successor. Each lane in a specific frame is represented by an individual (r, θ) pair. In the succeeding frame, the process will most probably observe the same lane at (r’, θ’) which is not very far from the position of the lane in the previous frame. The probability of observing (r’, θ’) pair in the next frame is modeled as an HMM problem. In addition, θ and r values are modeled by two different HMMs. The θ value is discretized as (0, 1, 2, 3. . . 178, 179) where the r value is discretized at the pixel level. This discretization schema is used in both transmission and emission matrices. The emission probability matrix shows the probability of observing θ’ (or r’) in the next frame, having observed θ (or r) in the current frame. In our implementation, the observation and state transition matrix values are derived from two Gaussian distributions with different deviations. The deviation of the transition matrix is assigned to a smaller value than the observation matrix, which means, the state transition matrix aims to preserve the current state where the observation matrix promotes the exploration behavior.

III. EXPERIMENTS

The approach proposed in this study is implemented and tested on a relatively short video sequence of an urban drive. In addition, the proposed approach is compared with the classical Hough transform where the entire image is processed and the most intense lines are accepted as candidate lines. The properties of the video are as follows.

Table 3.1. Properties of the video sequence.

Camera Position	Front Console of the Car
Resolution	512x288
Frame Rate	29.97
Length	34 Seconds

IV. SETUP

As the first step of the experiment, the image is converted to a binary image using a color remapping function. The mapping for each pixel from 24bit RGB value to binary value is given in Table 3.2.

Table 3.2. Color remapping.

Pixel Value	Red	Green	Blue
0-175	0	0	0
176-195	1	1	0
196-255	1	1	1

This binarization favors the white and yellow parts of the images. The values are manually crafted for the sample video. More discussions about improving the color remapping can be found in the next section.

The next step is to determine the partitions of the image on which the Hough transforms will be applied. Although the image is 288 pixels high, only the bottommost 116 pixels are used since the road remains in this lower part of the image. The accuracy of this assumption may slightly differ depending on the slope of the lane.

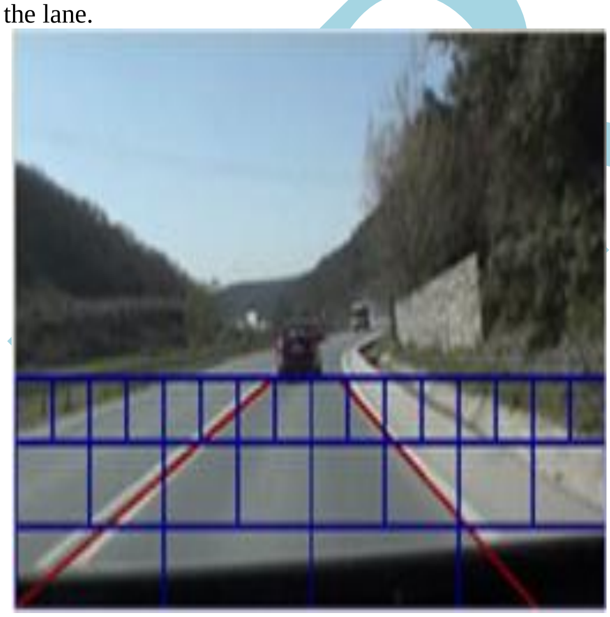

Figure 3.6. Image partitions.

The widths of the partitions are 32, 64, and 128 pixels from top to bottom. And the heights are 32, 42, and 42 pixels respectively as shown in Figure 3.6. These values are assigned according to the position of the camera. Exact dimensions of the partitions are not very crucial. The only idea is to put more attention on the far regions of the camera view. After the partitions are calculated, Hough transform is applied to each partition as described in the previous section. The most promising three lines are assigned as the candidate lane markings. But there may be less than three lines if the intensity of the calculated lines are less than an empirically assigned threshold. The experiment shows that the proposed approach usually detects only two lines most of the time.

After finding the lane markings, the HMM method is used to track the lanes. The values of the emission and state transition matrices are derived using Gaussian distribution. The deviation of the transition matrix is assigned as 1 and the deviation of the emission matrix is taken as 2. Two separate models are prepared for the θ and r values of the candidate lane markings. The transition and emission matrices are given in Tables 3.2.1 and 3.2.1. Since the θ values 0 and 179 are actually very close, the emission and transmission values are the same for 1 and 179 in θ matrices. In addition, the range of the r matrices is (0, 282) because the maximum possible distance for any detected line is 282 pixels where the height of the processed part of the image is 116 and width of the image is 512

V. RESULTS

The proposed approach managed to detect and track at least one lane in most of the sequence. In addition, false positives are reduced to an acceptable level. In order to validate the results, the proposed approach is compared with the classical Hough Transform approach. In this method, the same part of the image is processed using the Hough transform routine. The most intensive 10 lines are merged according to their r and θ values. Finally three or less candidate lines are selected as the lane markings.

The major differences between the classical and the multi-resolution HT are shown in Figure 3.7. The images on the left hand side are the detected or missed lines by the classical approach. The right hand side images are the outputs of the new approach for the same frames which show that the new approach is more robust and accurate. The computational cost of the proposed approach can be compared as follows. The average processing time is 21.25 milliseconds for a laptop PC with Intel T5450 processor at 1.66 GHz whereas the average time of the classical approach is 15.29 milliseconds.

Table 3.4. (a) Emission matrix for r, (b) Emission matrix for θ.

r	0	1	2	3	4	5	...	281	282
0	0.1995	0.1760	0.1210	0.0648	0.0270	0.0088	...	0.0000	0.0000
1	0.1760	0.1995	0.1760	0.1210	0.0648	0.0270	...	0.0000	0.0000
2	0.1210	0.1760	0.1995	0.1760	0.1210	0.0648	...	0.0000	0.0000
3	0.0648	0.1210	0.1760	0.1995	0.1760	0.1210	...	0.0000	0.0000
4	0.0270	0.0648	0.1210	0.1760	0.1995	0.1760	...	0.0000	0.0000
...	...	...	...	...	...	...	...	...	...
281	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	...	0.1995	0.1760
282	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	...	0.1760	0.1995

θ	0	1	2	3	4	5	...	178	179
0	0.1995	0.1760	0.1210	0.0648	0.0270	0.0088	...	0.1210	0.1760
1	0.1760	0.1995	0.1760	0.1210	0.0648	0.0270	...	0.0648	0.1210
2	0.1210	0.1760	0.1995	0.1760	0.1210	0.0648	...	0.0270	0.0648
3	0.0648	0.1210	0.1760	0.1995	0.1760	0.1210	...	0.0088	0.0270
4	0.0270	0.0648	0.1210	0.1760	0.1995	0.1760	...	0.0022	0.0088
...	...	...	...	...	...	...	...	...	...
178	0.1210	0.0648	0.0270	0.0088	0.0022	0.0004	...	0.1995	0.1760
179	0.1760	0.1210	0.0648	0.0270	0.0088	0.0022	...	0.1760	0.1995

Figure 5.1 Differences between classical Hough transform and proposed approach

VI. SIGN EXTRACTION

The aim of the sign extraction step is to extract the meaningful part of the sign from the circular of triangular frame surrounding it. We first perform a flood fill operation to convert the black regions around the 64x64 frame. As shown in Figure 4.16, the filling operation starts from the upper left corner of the frame. Next, a sanity check is performed to verify that the flood fill has only removed the surrounding black pixels, not the center of the frame. This may happen when all the black pixels are accidentally connected in the image. Especially, when the lighting conditions are poor, the detection step may yield frames with excessive amount of black pixels. After the flood fill operation we apply a second step of cleaning depending on whether the sign is circular or triangular.

Input: 24 bpp HSL color image and an array of target colors

Output: HSL image classified to target colors

foreach *pixel Pix* **do**

  foreach *target color* HSL_{target} **do**

    $Distance$ = ABS((HSL_{target}.H - Pix.H) mod 180) +

      ABS((HSL_{target}.S - Pix.S) x 180) +

      ABS((HSL_{target}.L - Pix.L) x 180);

  end

end

$Label_{Pix} = HSL_{target}$ with $Min_{Distance}$;

Figure 6.1 Generic HSL color labeling algorithm.

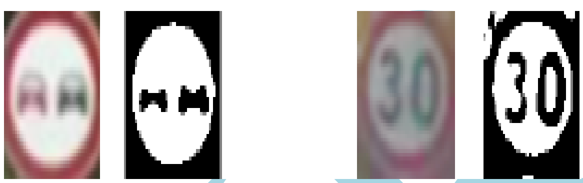

Figure6.2 Color labeling examples (black / white).

For the circular sigs, a circle of radius 24 is assumed to contain the interior part of the sign, and anything outside it is cleaned out. For the triangular case, a triangle as depicted in Figure 4.16 is assumed to surround the meaningful part of the sign. All pixels outside this virtual triangle are cleaned out.

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